Go With The Flow: A New Manifold Modeling and Learning Framework for Image Ensembles

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Image processing in the internet age benefits immensely from massive databases of images and videos such as FlickR and Youtube. A large class of difficult computer vision and image understanding problems (including video summarization, automated image annotation, and localization) can be solved by learning information from image ensembles via crowd-sourcing. When an image ensemble is generated by varying a small number of imaging parameters or camera articulations, it is endowed with an additional geometric structure, namely that it can be modeled as a low-dimensional image articulation manifold (IAM). The geometrical properties of the IAM encode the physical attributes of the scene under view; presumably these attributes can be accessed using differential geometry on the IAM.

A host of manifold-based processing and learning algorithms have been developed around this presumption, but unfortunately they suffer from one or more of three major shortcomings. First, current manifold processing methods assume that the image manifold is isometric to the parameter space; this assumption is violated by realistic images with textures. Second, locally linear methods that are based on a tangent space approximation to the manifold generally apply only in an extremely small neighborhood around each point on the manifold and thus can fail to capture important curvature properties of the IAM. Third, algebraic methods, while powerful in theory, require that the manifold possess an unrealistic algebraic (e.g., Lie group) structure.

In this talk, we leverage recent advances in the theory and practice of sparse and dense image correspondences to circumvent these shortcomings. We propose a new framework for modeling IAMs based on the notion of a transport operator that maps one image point an IAM to another. We observe that the optical flow between pairs of images on an IAM serves a natural and well-behaved transport operator. We establish that the space of optical flows is itself a low-dimensional smooth manifold, which enables new analytical tools for modeling, navigating, and processing IAMs. A key hallmark of our approach is that it applies to images with complex textures as well as articulations that are modeled by non-rigid and/or unstructured deformations. Numerous experiments involving novel-view synthesis, spatial and temporal super-resolution, geometric clustering, and manifold charting validate that our new framework offers significantly superior performance to existing methods.

This is joint work with Aswin Sankaranarayanan, Chinmay Hegde, and Sriram Nagaraj